

A Response-by-Retrieval Chatbot for Enhancing Horticulture Extension Services in Tanzania

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Received: 16 June 2025 | Revised: 11 July 2025, 14 July 2025, and 20 July 2025 | Accepted: 23 July 2025

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ABSTRACT

Horticulture, which encompasses the cultivation of flowers, fruits, herbs, and vegetables, is a key contributor to Tanzania's export revenue generation. Smallholder farmers are the primary producers of these crops, and they rely heavily on extension services for critical information that shapes both their economic success and long-term sustainability. However, the delivery of such services from the government and other stakeholders faces challenges, including constraints in human capital, geographic barriers, misaligned information needs, as well as issues with the timeliness of information dissemination. To address these challenges, this study developed a Swahili-language chatbot designed to provide timely, context-specific information tailored to the needs of farmers. To ensure credibility and relevance, key private and public stakeholders were consulted, and comprehensive farming guides were collected to build a custom dataset. This dataset consisted of 307 passages and 2,231 question-answer pairs. Four multilingual models, Multilingual Bidirectional Encoder Representations from Transformers (mBERT), Cross-lingual Language Model Pretraining RoBERTa (XLM-R), Multilingual Decoding-Enhanced BERT with Disentangled Attention (mDeBERTa), and Afro Cross-lingual Language Model Pretraining RoBERTa (AfroXLMR), were finetuned on this dataset for a question-answering task. Among them, the mDeBERTa model achieved the strongest performance, with an Exact Match (EM) score of 62.69% and an F1 score of 75.35%. These results demonstrate the potential of adapting advanced language models for specialized, low-resource language tasks in agriculture. The deployment of mDeBERTa in a prototype chatbot highlights a promising pathway to bridge information gaps and enhance the accessibility of extension services for Tanzania's smallholder farmers.

Keywords-chatbot; natural language processing; question-answering; Bidirectional Encoder Representations from Transformers (BERT)

I. INTRODUCTION

Horticulture is an agricultural sub-sector that involves the cultivation of plants such as vegetables, fruits, and herbs [1]. In Tanzania, it has shown strong growth, maintaining an annual uptrend of 12%, which is three times higher than the overall agricultural sector growth of 4% [2]. For the financial year ending June 2022, horticultural exports generated USD 369.1 million, with edible vegetables and fruits contributing USD 295.4 million and USD 19.4 million, respectively [3]. Recognizing this potential, the government launched a national horticultural development strategy aimed at meeting the rapidly growing domestic and international demand [4]. One of its key targets is to raise horticultural exports to USD 2 billion within five years. To achieve this, the government has partnered with the Tanzania Horticulture Association (TAHA) to strengthen research and development, market access, and the delivery of accurate and seamless information to farmers [5].

Smallholder farmers are the backbone of horticultural production in Tanzania. Typically owning farms of less than two hectares, their productivity and profitability depend heavily on access to accurate knowledge and timely information [6]. Extension services play a crucial role in this regard by transferring good practices and providing advisory support to farmers [7]. These services are subsidized by government extension officers; however, a national survey reported that only 7% of crop-growing households had received such services [8]. To address these gaps, various Information and Communication Technology (ICT)-enabled extension services have been introduced [9]. For instance, Esoko is a digital platform designed to expand farmers' access to market and extension information through internet technologies [10]. Similarly, the government's Mobile Agriculture (M-Agriculture) initiative enables farmers, breeders, and fishers to access market information via mobile phones [11]. Other innovations include Ushauri, a mobile advisory service for sustainable intensification [12], and a web portal for decorative plants and flowers that facilitates species mapping and digitization [13]. Despite their promise, these solutions remain constrained by static user experiences, poor feedback mechanisms, misaligned information needs, and delays in dissemination [14].

In recent years, chatbots, conversational agents that interact with users in natural language, have emerged as a potential solution [15]. They are generally categorized into template-based and Artificial Intelligence (AI)-based systems [16]. AI-based chatbots can further be divided into retrieval-based and generation-based models [17]. Retrieval-based systems rely on algorithms such as Term Frequency-Inverse Document Frequency (TF-IDF), Best Match 25 (BM25), and Dense Passage Retrievers (DPR) to retrieve the most relevant responses from a predefined knowledge base [18], while generation-based models can synthesize novel responses beyond fixed datasets.

Several chatbot systems have been developed for agriculture. For instance, FarmChat was built for rural Indian potato farmers, combining Google's Speech-to-Text and IBM Watson for intent recognition; however, it relied on a limited

knowledge base and proprietary Natural Language Processing (NLP) services [19]. AgriBot used a sentence embedding model (Sen2Vec) trained on the Kissan Call Center (KCC) dataset to handle farmer queries, with entity extraction for efficiency; yet, it only supported English and struggled with specific queries [20]. A Naïve Bayes-based chatbot for soil and crop fertility advice was also proposed, but its probabilistic approach was inadequate for handling complex natural language contexts [21]. Authors in [22] proposed Agroxpert-Farmer Assistant, powered by the Chatterbot library, to provide timely information and support farmers [22]. The chatbot, trained on predefined responses, used the Levenshtein distance and best-match algorithm to process and respond to user queries. However, its effectiveness was hindered by its pattern-matching techniques when it came to non-standard queries. Authors in [23] developed CropGuard, an AI-driven chatbot to help farmers detect plant diseases in potatoes and tomatoes. Combining image classification, conversational AI, and data-driven insights, it enhanced disease detection and management. The image classification model was based on ResNet50 architecture, and conversational AI was powered by GPT-3.5 Turbo. However, the chatbot's capabilities were handled by a proprietary language model accessible only through an Application Programming Interface (API).

Despite these developments, significant gaps remain for horticultural extension services in Tanzania, with existing solutions relying heavily on proprietary systems, traditional machine learning methods, or limited language support. Furthermore, many are not holistic, focusing only on specific farming stages rather than the full production cycle. This study addresses these challenges by developing a retrieval-based chatbot finetuned on a custom Swahili-language horticultural dataset. Unlike earlier solutions, it provides localized, context-specific information covering all stages of horticultural production, from preliminary preparations to post-harvest practices, while ensuring accessibility for Tanzanian smallholder farmers who primarily communicate in Swahili.

II. MATERIALS AND METHODS

A. Dataset

1) Dataset Availability

The dataset used in this study is available in the Harvard Dataverse online repository. It is provided in Swahili, accompanied by a separate file containing an English translation generated with Google's Cloud Translation API. The dataset is publicly accessible at [24].

2) Dataset Preparation

Relevant documents on horticultural cultivation and existing solutions were collected and analyzed for applicability, credibility, accessibility, and comprehensiveness. Two key stakeholders in the horticultural sub-sector were identified as primary sources: the Sokoine University of Agriculture (SUA) and the TAHA. Both institutions maintain open-access repositories, including the Mkulima repository at SUA and the TAHA Resource and Information Center (TARIC), which were utilized in this study. A total of 52 documents concerning fruit, spice, and vegetable cultivation were selected, with emphasis

on availability in Swahili, the predominant language among the target audience. The selected documents also covered the complete farming process. Consent was obtained from both institutions to use these open-source documents. To ensure accuracy and relevance, the documents were reviewed and validated by two horticultural extension officers.

3) Dataset Preprocessing

The collected farming guides, originally in Microsoft Word (.docx) and Portable Document Format (.pdf), were standardized to ensure consistency in file format. Each document was converted to plain text (.txt), followed by a cleaning process that removed empty spaces, tags, images, figures, and tables. The cleaned versions were cross-checked against the originals to ensure no critical information was lost during conversion.

4) Dataset Development

The dataset was created by extracting textual contexts from the documents, with each context containing at least 500 characters to ensure sufficient informational content for the task. Four annotators were tasked with generating context-question-answer triplets using the Haystack annotation tool. This process was facilitated by setting up four local machines to run the tool's Docker image. The tool enabled efficient document uploads, the generation of question-answer pairs, and the export of annotated data in formats compatible with both the Stanford Question Answering Dataset (SQuAD) and tabular structures.

Following the methodology outlined by [25], annotators were instructed to create questions that extracted specific information from the corresponding passages, ensuring the answers were explicitly present. Questions were phrased with varied wording, synonyms, and abstract formulations to avoid simple repetition of the text. The final dataset comprised 307 passages and 2,231 question-answer pairs. It was exported in JavaScript Object Notation (JSON) and Comma-Separated Values (CSV) formats, making it ready for model training.

B. Experiment Setup

The experiment setup was configured on a laptop running Microsoft Windows 11, version 23H2, equipped with a 12th Generation Intel® Core™ i5-12500H processor (2.5 GHz) and 32 GB Random Access Memory (RAM). Python served as the programming language for the implementation of the models. For Graphical Processor Unit (GPU) provisioning, the Google Colaboratory platform was used, where the four multilingual models were trained on a V100 High-RAM GPU runtime. After training, the models were uploaded to the Hugging Face platform to facilitate inference tasks as well as to make the models accessible to other researchers and practitioners for further experimentation and analysis.

C. Model Training

Four multilingual models were fine-tuned on the dataset created for the question-answering task: Multilingual Bidirectional Encoder Representations from Transformers (mBERT), Cross-lingual Language Model Pretraining RoBERTa (XLM-R), Multilingual Decoding-Enhanced BERT with Disentangled Attention (mDeBERTa), and Afro Cross-

lingual Language Model Pretraining RoBERTa (AfroXLMR). These models were selected due to their pretraining on multilingual corpora that included Swahili, accessibility, and suitability for fine-tuning. Other multilingual such as mT5, RemBERT, BLOOM, were considered but excluded due to computational inefficiency, large model size, or latency. Additionally, AfroXLMR was specifically included as it was trained on an African-centric dataset, offering stronger Swahili representation.

Training was conducted in two phases: first with off-the-shelf versions of the models, and then with fine-tuned versions pretrained on the SQuAD benchmark. The number of training epochs was set to 50, with checkpoint monitoring implemented to reduce overfitting. Table I summarizes the configuration of the models fine-tuned on SQuAD.

TABLE I. MODEL CONFIGURATION

	AfroXLMR	mBERT	mDeBERTa	XLM-R
Vocabulary size	250,000	250,000	250,000	250,000
Document stride	128	128	128	128
Maximum sequence length	256	384	384	256
Learning rate	5e-5	2e-5	2e-5	2e-5
Hidden size	768	768	768	768
Hidden layer size	12	12	12	12
Epochs	3	3	3	3
Base model	afro-xlmr-base	bert-base-multilingual-cased	mdeberta-v3-base	xlm-roberta-base

D. Model Evaluation

Model performance was evaluated using the Exact Match (EM) and F1 score metrics. The EM metric is calculated by taking the percentage of the model predictions that match the true answers exactly [25]. The emphasis of the metric is exactness in answers, quantifying how often a model's response matches the ground truth word-for-word. The F1 score evaluates word overlap between predicted and labeled answers, treating them as bags of words.

E. Deployment

An evolutionary prototyping approach was adopted to develop and refine a web-based prototype. This initial prototype was presented to a select group of smallholder farmers and incorporated their feedback into successive versions of the prototype. This iterative process continued until the farmers were satisfied with the final version.

The prototype used a client-server architecture with a two-tier design. On the client side, the Chainlit framework created the chat interface, while the server side was powered by FastAPI. Weaviate, a vector database optimized for word embeddings, handled data management. Additionally, the Haystack open-source framework, known for orchestrating natural language applications, was used to create an extractive question-answering pipeline. This pipeline integrated a dense embedding-based retriever with a reader component. The

retriever used Cohere's Embed v3 text embedding model, which was selected for its state-of-the-art performance on the Massive Text Embedding Benchmark (MTEB) and Benchmarking Information Retrieval (BEIR) [26].

III. RESULTS AND DISCUSSION

A. Model Performance Results

The performance results of the off-the-shelf versions and finetuned multilingual models are summarized in Table II. The mDeBERTa model demonstrated higher performance across both evaluated metrics in the two phases of training. In the first phase, it achieved an EM of 53.0% and an F1 score of 67.3%, while in the second phase, it achieved an EM of 62.7% and an F1 score of 75.4%. In contrast, the mBERT model achieved an EM of 39.0% and an F1 score of 49.9% in the first phase, and an EM of 46.7% and an F1 score of 58.6% in the second phase. The AfroXLMR and XLM-RoBERTa models recorded intermediate results, demonstrating noticeable improvements when fine-tuned but not surpassing mDeBERTa.

TABLE II. EVALUATION RESULTS

Model	EM (%)	F1 Score (%)
AfroXLMR	41.9	52.4
mBERT	39.0	49.9
mDeBERTa	53.0	67.8
XLM-R	40.4	52.3
AfroXLMR+finetuned	55.4	68.1
mBERT+finetuned	46.7	58.6
mDeBERTa+finetuned	62.7	75.4
XLM-R+finetuned	51.8	65.1

B. The Developed Prototype

The generalized workflow of the prototype is shown in Figure 1. When a user submits a query through the chat interface, the request is first received by the FastAPI backend. The query is then processed by the embedding retriever to

generate a query embedding, which is then matched against passage embeddings stored in the Weaviate vector database. The most relevant passages are retrieved and passed to the question-answering model via the Haystack pipeline, where the model extracts the final answer. This response is returned to the user through the FastAPI interface.

The web-based prototype included a welcome page explaining the chatbot's purpose and the specific crops it can provide information on. As shown in Figure 2, the chat interface allowed users to pose questions and, if desired, cross-reference the chatbot's responses with the extracted supporting context for transparency.

The prototype was evaluated with 20 smallholder farmers, who assessed it on four criteria: overall usefulness, clarity of responses, accuracy in answering, and ability to understand question context. Each criterion was rated on a five-point scale: very high, high, satisfactory, low, and very low. The aggregated results of the farmers' feedback are presented in Figure 3, showing generally positive responses, with most participants rating the system as either high or very high across the four dimensions.

C. Discussion

The baseline performance results revealed that the mBERT model achieved only modest outcomes, which is likely attributable to its generalized pre-training that does not transfer effectively to low-resource datasets. Similar below-average results for mBERT have been reported in prior studies. For instance, authors in [27] reported an F1 score of 41.2% in their study on conversational Question Answering (QA) for low-resource scenarios. Likewise, authors in [28] evaluated mBERT on the MLQA dataset for Arabic and Hindi and reported EM/F1 scores of 29.8%/45.7% and 29.7%/43.8%, respectively. These findings suggest that while mBERT provides broad multilingual coverage, its performance in specialized low-resource settings remains limited.

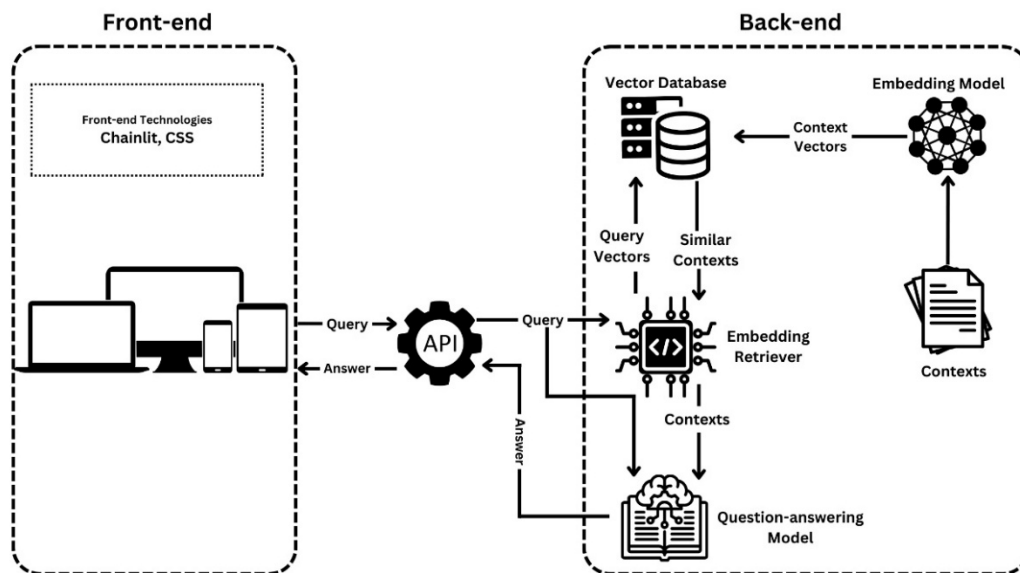


Fig. 1. System overview.

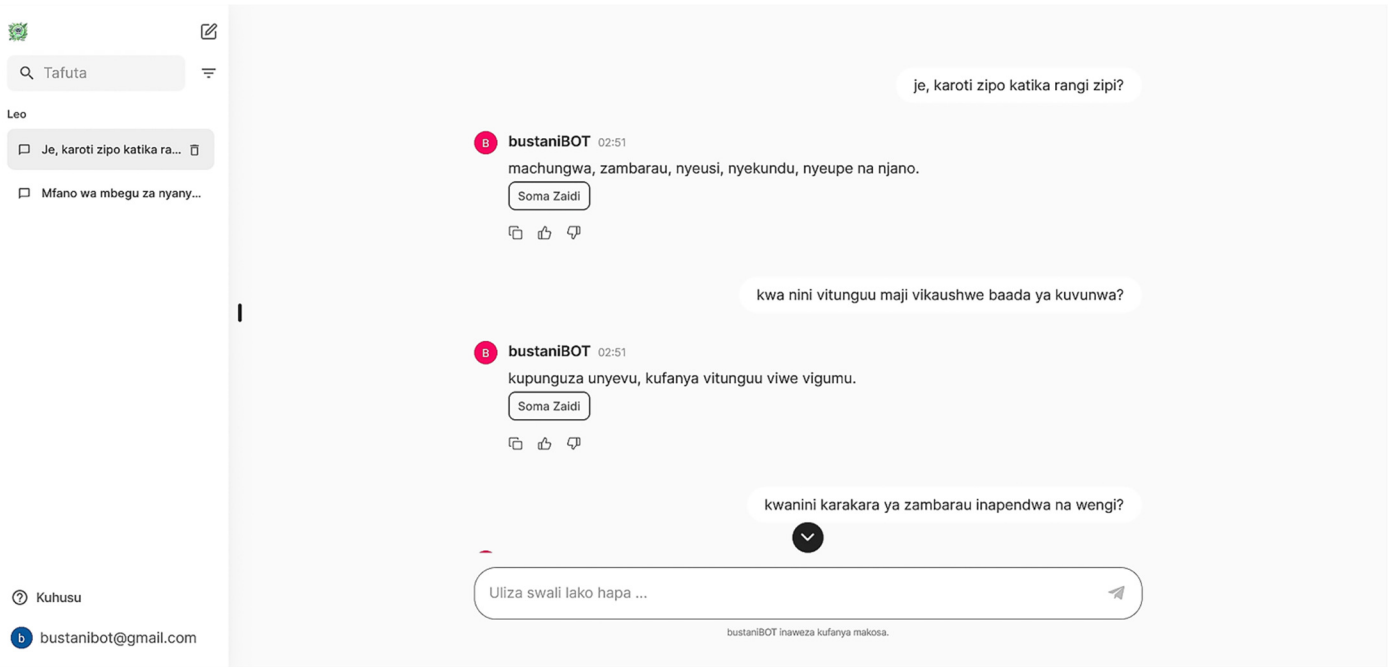


Fig. 2. Chat interface.

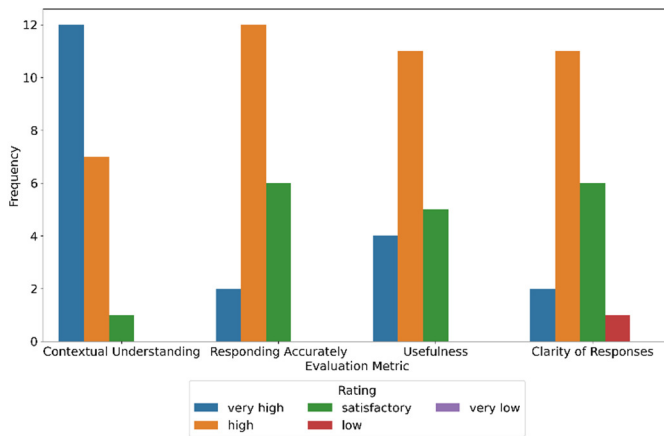


Fig. 3. Smallholder farmers' evaluation.

The AfroXLMR and XLM-R models demonstrated intermediate results in this study, with performance levels close to each other despite AfroXLMR being enhanced through Multilingual Adaptive Pre-Training (MAPT) specifically for low-resource languages. This indicates that while MAPT may offer some benefits, the XLM-R backbone remains more robust for comprehension tasks. This observation is consistent with the study in [29], which introduced a reading comprehension dataset in Tigrinya and found that the XLM-R base model achieved comparable results, with an EM of 46.2% and an F1 score of 68.1%, aligning closely with the outcomes of our study. In contrast, the mDeBERTa model clearly outperformed all other baselines, which can be attributed to its architectural innovations. Unlike mBERT, which uses a single vector for its attention mechanism, mDeBERTa employs two disentangled vectors, one for word embeddings and another for position embeddings [30]. This structural enhancement allows it to

better capture contextual dependencies, leading to significant performance gains.

The fine-tuned versions of the multilingual models further underscored the effectiveness of task-specific adaptation. Both AfroXLMR+finetune and XLM-R+finetune showed marked improvements. Interestingly, AfroXLMR+finetune achieved substantial gains, in some cases surpassing the mDeBERTa+finetune model. This stands in contrast to the results reported in [31], where AfroXLMR was evaluated on an Afrocentric cross-lingual QA dataset and achieved only 37.9% EM and 45.2% F1 score for Swahili, with overall averages across 10 languages of 42.4% EM and 52.4% F1 score. On the other hand, the performance of our XLM-R+finetune is consistent with the study in [32], which reported EM/F1 scores of 47.5%/64.5% on the Amharic QA dataset.

IV. CONCLUSION

This study developed a response-by-retrieval chatbot to enhance horticultural extension services in Tanzania. The chatbot employed a multilingual embedding retriever and was supported by the creation of a custom Swahili question-answering dataset, consisting of 307 passages and 2,231 question-answer pairs. The dataset fills a critical gap caused by the limited availability of high-quality, domain-specific Swahili resources and can serve as a valuable asset for researchers and practitioners in Natural Language Processing (NLP). Future expansion may leverage semi-supervised learning, data augmentation, or crowdsourcing to improve its scale, diversity, and coverage.

Four multilingual models, Multilingual Bidirectional Encoder Representations from Transformers (mBERT), Cross-lingual Language Model Pretraining RoBERTa (XLM-R), Multilingual Decoding-Enhanced BERT with Disentangled Attention (mDeBERTa), and Afro Cross-lingual Language

Model Pretraining RoBERTa (AfroXLMR), were finetuned on the custom dataset for the question-answering task. Among these, mDeBERTa consistently outperformed the others across evaluation metrics, demonstrating the potential of adapting advanced language models to low-resource, domain-specific applications. Its integration into a working prototype illustrates a practical pathway for bridging information gaps faced by smallholder farmers in Tanzania.

The study acknowledges that the annotations of the custom dataset were done by a limited number of annotators, so there may be inherent biases and systematic annotation errors. Additionally, the chatbot responses were limited to single-turn interaction. Future studies can explore alternative chatbot development approaches, such as response-by-generation, along with advanced techniques like Retrieval-Augmented Generation (RAG), which could further enhance performance. Additionally, future studies on the vectorization of monolingual Swahili text are recommended, as they may significantly enhance the efficiency and accuracy of embedding-based retrievers.

ACKNOWLEDGMENT

This work is supported by the Artificial Intelligence for Development Africa Program, a program funded by Canada's International Development Research Centre and the Swedish International Development Cooperation Agency, grant number 109704-001/002. The authors would like to thank Ms. Belinda Masawe, Ms. Elizabeth Canan, and Mr. Noel Ngatunga for their valuable assistance during dataset creation.

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